# Learning Physically Informed Maps for Off-world Autonomous Scientific Discovery

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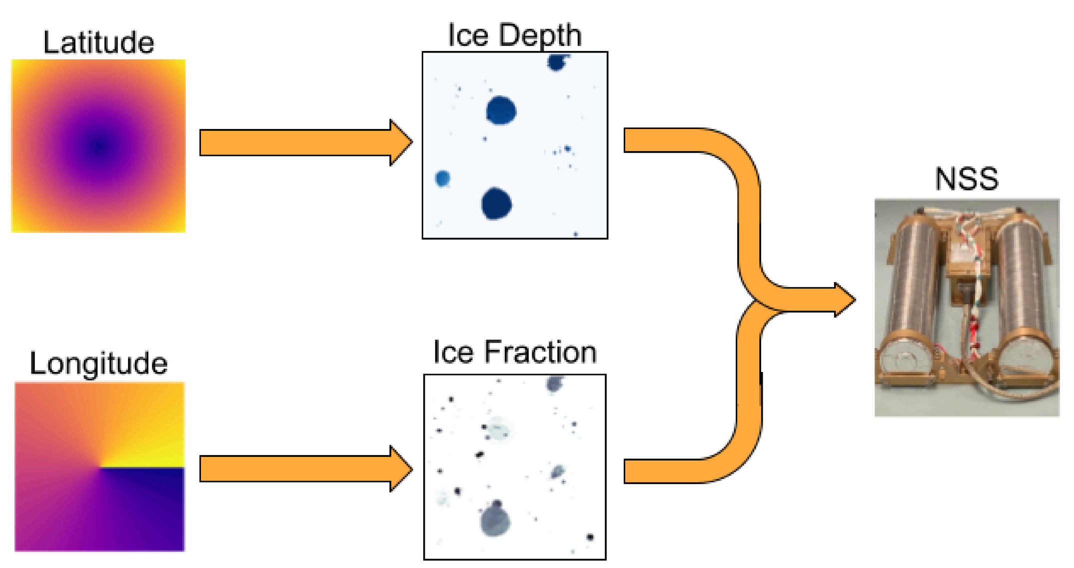
## Motivation

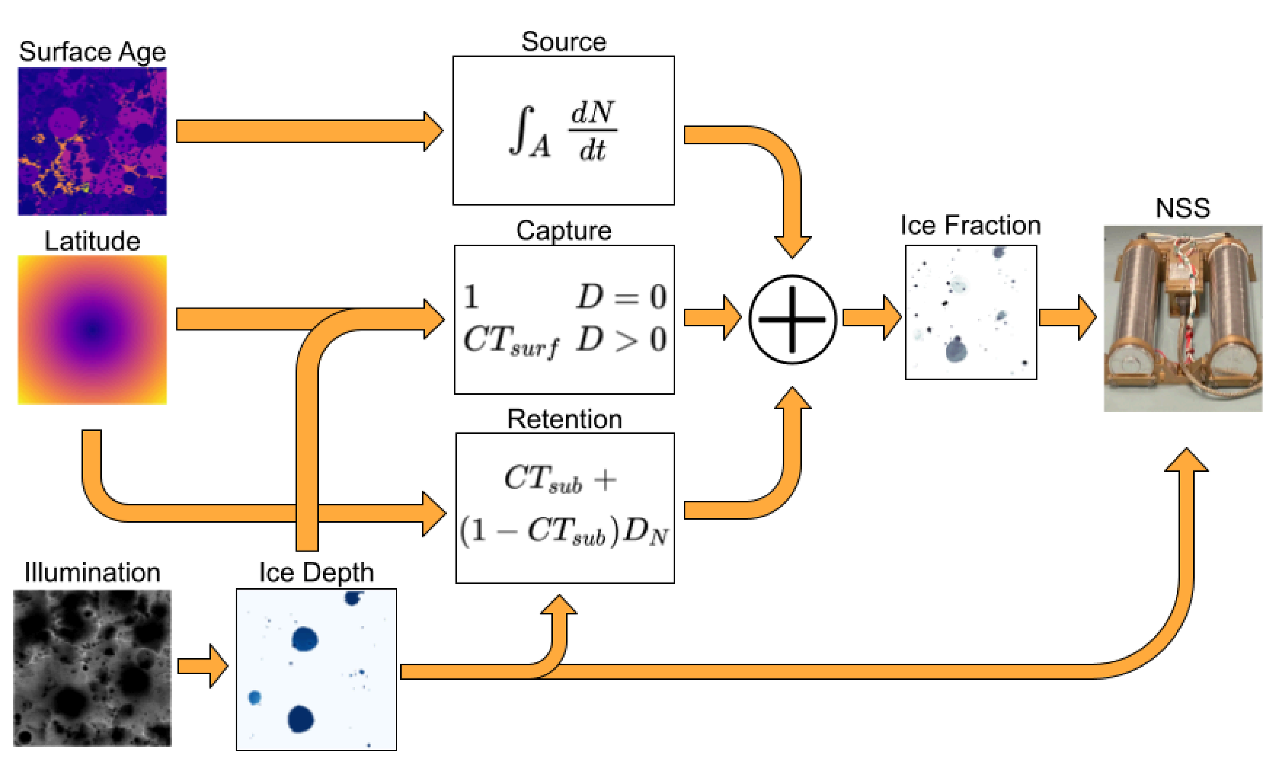
Integrating information into maps enables adaptive reasoning about physical processes

## Methods: Deep Gaussian Processes

Simple Deep Model: Latent values from one GP per spatial input




Full Deep Model: Hierarchy of GPs based on physical knowledge




## Methods: Sensor Loss

Additional loss term from neutron spectrometer (NSS) sensor model

$$\mathcal{L} = \mathcal{L}_{GP} + \mathcal{L}_{NSS}$$

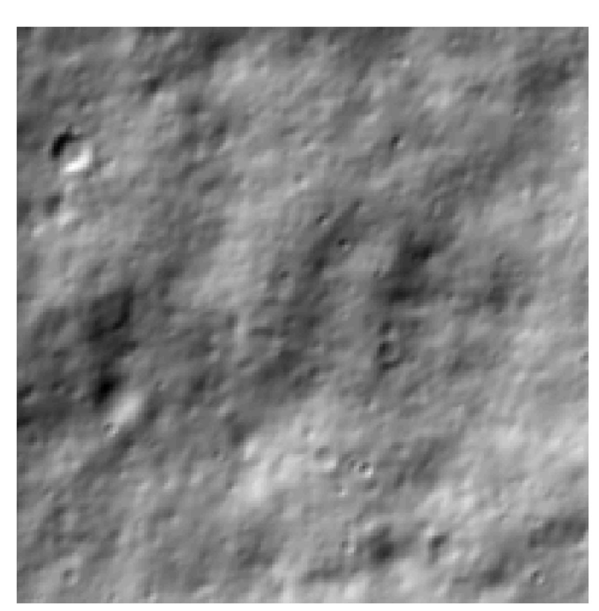
$$\boxed{-\log(P(\mathbf{y}|X))} \quad \boxed{\frac{1}{N}\sum_{i=0}^{N}(\mathbf{y} - \hat{\mathbf{y}})^2}$$

## Baselines

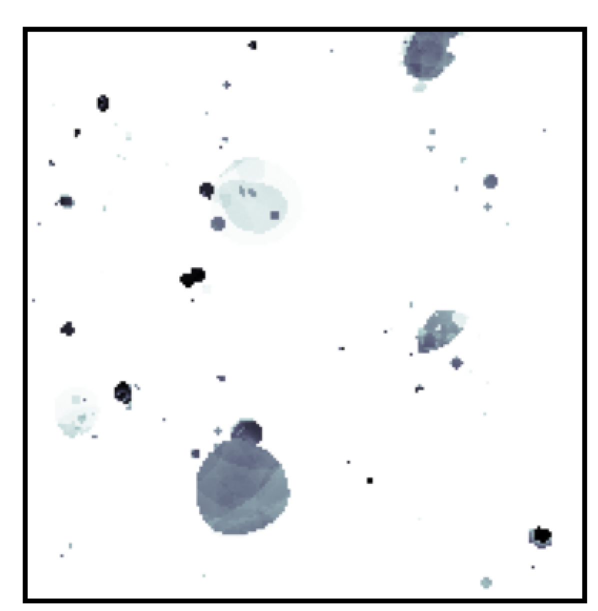
- Standard GPs with spatial and/or process variable (PV) predictors
- Multi-output GP predicting observations and PVs (MOGP)

## Dataset

Simulated lunar surface and volatiles over geologic time



Surface



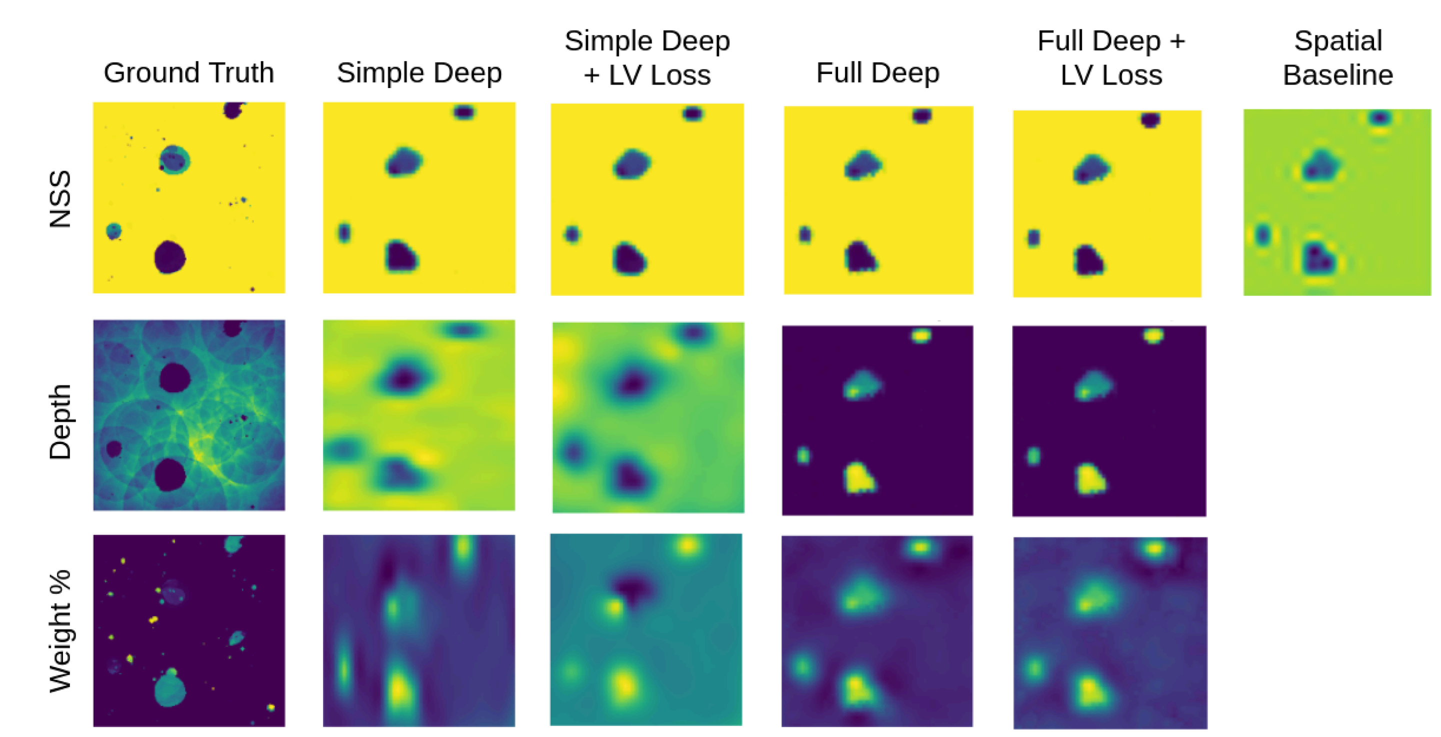
Ice Weight Fraction

## Results

Physically informed maps exhibit:

- Lower map error
- Ability to model indirectly-observed quantities of interest (depth, weight fraction)

| Model | NSS MAE (↓) | Depth MAE (↓) | Wt % MAE (↓) |
|---|---|---|---|
| Spatial Baseline | 0.8374 | – | – |
| PV Baseline | 1.8669 | – | – |
| Spatial + PV Baseline | 0.8601 | – | – |
| MOGP Baseline | 0.9448 | – | – |
| Simple Deep | 0.4386 | 1.6260 | 0.0565 |
| Simple Deep + LV Loss | 0.4134 | 2.9709 | 0.0750 |
| Full Deep | 0.4540 | 1.8914 | 0.1080 |
| Full Deep + LV Loss | 0.4584 | 2.5425 | 0.0735 |

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